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Role of Behavioral Economics in Diagnostics Delays and Errors

1. Introduction

Making health decisions is often a complex task requiring accurate judgment of risk and benefits of many alternatives. Moreover, risks are inherently difficult to subjectively perceive, compare, and communicate accurately and have been extensively studied in cognitive psychology for decades. The process of judgment and decision making can lead to diagnostic errors and delays by health providers and suboptimal patient decisions about their health. Diagnostic errors account for most medical errors and can lead to excessive deaths in the US each year. These diagnostic errors are especially prevalent and consequential in infections, acute vascular events, and cancer.

The field of behavioral economics, which integrates psychology and economics, can provide insights on human behavior that explain and predict diagnostic errors and delays. Behavioral economics investigates the role of psychological, social, cognitive, and emotional factors on decision making and human behavior. These factors can also be leveraged to design and evaluate interventions that improve medical and health decisions and subsequently clinical outcomes (Loewenstein et al., 2007; Matjasko et al., 2016; Patel & Volpp, 2012; Skinner & Volpp, 2017; K. G. Volpp & Asch, 2017; Kevin G. Volpp et al., 2011; Waddell et al., 2020). Behavioral economics interventions require targeting clearly defined clinician or patient behaviors, such as performing or recommending a routine cancer screening based on medical guidelines. As such, most research in the field is focused on such behaviors from flu vaccination to adherence to cancer screening guidelines.

This paper describes behavioral frameworks (e.g., cognitive biases and choice architecture) and relevant literature on the role of behavioral insights in human judgments and decisions that can lead to diagnostic delays caused by both patients and providers. For patients, most evidence is concentrated on delays due to underutilization of preventive health measures such as routine cancer screening. For providers, misdiagnoses or misinterpretation of symptoms can result in delays and failure to recommend follow-up tests. The paper also provides examples of various data sources (e.g., electronic health record (EHR), patient-reported data) and experimental designs (e.g., randomized controlled trials (RCT)) used in behavioral economics research to explain and prevent diagnostics delays. To support health equity, this paper also examines the interaction between behavioral economics research and social determinants of health (e.g., psychology of scarcity).

This paper should be considered as a form of a narrative review, as we have conducted a literature search and summarized the role of behavioral science concepts in relation to preventive health actions and diagnostic errors and delays in cancer, infections, and acute cardiovascular events. While behavioral economics principles apply widely across many medical domains, empirical research in some areas might be scarce due to inability to conduct behavioral research and other constraints. When examples in these three areas were unavailable, we have included a theoretical prediction as well as the most relevant evidence we could identify to stimulate future research.

2. Behavioral economics and health.

Even in the context of health decisions, standard economic theories assume that people are rational, self-controlled, self-interested, and ever-optimizing (Loewenstein et al., 2007). In fact, people's rationality is bounded (Simon, 1972) and influenced by a variety of factors outside of the standard economic model. Physicians, and other experts, are often biased to the same degree as laypeople (Blumenthal-Barby & Krieger, 2014; Saposnik et al., 2016). Research in behavioral science and cognitive psychology over the last 50 years documented and explained deviations from optimal behavior in a variety of domains from finance to health. Research in behavioral economics often concludes with a set of recommendations that can improve decisions and result in greater health and happiness. Due to the promise of improved decisions and outcomes, medical research has increasingly integrated behavioral economics principles into medical decision making and health behaviors (Kevin G. Volpp et al., 2006, 2008).

One of the most famous examples of such research is the colonoscopy study by Redelmeier, Katz and Kahneman (2003). In the study, they illustrate the counterintuitive role of psychological factors and effect on human judgment of pain and memory and the long-term effect of such judgments. In the randomized controlled trial, they found that participants who have undergone a longer colonoscopy recall the procedure as *less* unpleasant than those who have undergone a *shorter* procedure. Patients who were randomized to the longer treatment also indicated higher willingness to repeat the treatment in the future. Similar findings were documented among patients who have undergone lithotripsy (Redelmeier & Kahneman, 1996). These examples illustrate how imperfect and biased memory can impact future decisions and the use of preventive health behaviors.

3. Biases Framework

Psychology of judgments and decision making investigates the way information is processed and the effect on objective criteria on judgments and decisions in numerous contexts. Heuristics, also called cognitive shortcuts, exist to improve the efficiency of information processing. These heuristics are especially useful under time and attention constraints because they provide shortcuts to quick decisions. However, heurists often lead to cognitive biases – systematic and predictable errors in judgment that result from reliance on heuristics (Tversky & Kahneman, 1974). In the decades since the seminal work by Tversky and Kahneman (1974) research has consistently confirmed the effect of heuristics on error in judgments and identified additional heuristics that further explain the complexity of human judgment.

In the medical profession, decisions are often made under extreme time pressures due to a medical emergency or as a result of a system that limits interaction time with a single patient. Under these constraints, physicians are expected to gather information and make correct and life-critical judgments. Quality of decisions can also change over the course of a shift or a session due to decision fatigue. Ominously, biased-based judgments, including unconscious racial bias, can become more vivid when faced with decision fatigue as has been shown among clinicians and general population (Meeker & Doctor, 2017; Van Ryn, 2002). Despite the common perception that expertise is immune to these cognitive biases, researchers have repeatedly illustrated that experts, including clinicians, are not exempt from biased-based judgments that often can lead to diagnostic inaccuracies and medical errors (Blumenthal-Barby & Krieger, 2014; Hugh & Dekker, 2009; Saposnik et al., 2016). One systematic review suggested that common cognitive biases, including availability bias, were associated with physicians' diagnostic inaccuracies in up to 77% of case scenarios (Saposnik et al., 2016).

On the patient side, everyday demands of life often contribute to underestimation of health risk and underutilization of preventive healthcare. This is evident in public risk perception of cancer, cardiovascular diseases, and infections (Brewer et al., 2007; Everett et al., 2016; Ferrer & Klein, 2015; Homko et al., 2008).

In this section, we argue for the need to understand when and how cognitive biases can result in delay in diagnosis. We focus on a non-exhaustive list of five biases that are most relevant for the research question of this paper: availability bias, affect heuristic, status quo bias, present bias, and information avoidance. In Table 1, we define each bias, provide examples of a biased-driven error in judgments by both physicians and patients, and illustrate possible solutions. Our discussion of solutions will be expanded in the next section on choice architecture.

Table 1. Cognitive biases: definitions and examples from physician and patient perspective.

Concept	**Definition**	**How Can it Impact Physicians?**	**How Can it Impact Patients?**	**Possible Solution**
Availability bias	Overestimating the likelihood of an event (disease) based on how promptly an example comes to mind	Not implementing a comprehensive cardiotoxicity risk assessment prior to cancer treatment	Underestimating risks of cancer or cardiovascular diseases due to limited information or prior exposure	Deliberate reflection on risk and probabilities of diseases and increasing awareness about diseases risks
Affect heuristic	Emotional associations influence risk perception and shape decisions	Affective response to previous interactions can influence decisions for future patients	Description of cancer in an emotional manner can increase risk perception of cancer risk	Provide alternative choice setting that encourages rational decision making with minimal affective influence
Status Quo bias	Preference for the current situation or things to stay the same	Low referral for diagnostic tests due to the need to actively choose such tests	Not participating in health screening due to the need to actively schedule an appointment	Setting a desired choice as the default option with possibility to opt out
Present bias	Preferences for immediate outcomes and discounting long-term outcomes	Deprioritizing symptoms or possible disease (cardiovascular diseases) in order to address immediate condition	Neglecting recommended physical activity or healthy diet	Providing information on alternative to current set of actions and rewarding for desirable behaviors
Information avoidance	Tendency to avoid accessing information even when information is available and free	Might avoid information that is inconsistent with previous diagnosis (also called confirmation bias)	Avoiding uptake of preventive healthcare measure to avoid potentially negative information	Communicating health information even in the absence of active choice to seek information

3.1. Availability bias

The availability bias (also called availability heuristic) explains why people make errors in estimating likelihood of an event that is happening based on how easily an example or specific event comes to mind (Tversky & Kahneman, 1974). In other words, people assign too much weight to examples that come to mind easier, mostly because they are the most recent examples and therefore come to mind quickly. In line with availability bias, diseases or medical conditions that are commonly covered by the news or faced by close family members are perceived as more likely and riskier to the individual. As in many other biases, errors in judgment driven by availability bias do not omit experts, including physicians. Several examples have been reported in the literature. In a study of medical decision making, research has shown that physicians who recently encountered bacteremia in a patient were more likely to diagnose the condition in future patients (Poses & Anthony, 1991). Experience can also increase bias. One study has found errors in diagnosis driven by availability bias among second-year residents but not among first-year residents (Mamede et al., 2010). Specifically, when presented with a patient who is experiencing symptoms similar to a previously seen patient, second-year residents were more likely to make an error in diagnosis than first-year residents (Mamede et al., 2010).

However, as noted in a systematic review (Blumenthal-Barby & Krieger, 2014), a majority of studies examining impact of cognitive biases in the context of medical decisions were based on hypothetical scenarios, which might raise concerns about applicability of these findings to real-world decision making. Authors also noted that biases and heuristics have been under investigated among medical specialists as compared to patients (Blumenthal-Barby & Krieger, 2014).

There are some studies, however, that have investigated the role of availability heuristics and physicians' real choices. For example, studies have found availability heuristics to be associated with physicians' medication prescribing behaviors (Choudhry et al., 2006), screening recommendations (Keating et al., 2017; Ly, 2019, 2021), and decisions made in the delivery room (Singh, 2021). Choudhry et al., (2006) investigated whether adverse events associated with prescribing a blood thinner medication (warfarin) for patients with atrial fibrillation affected future prescribing, finding that physicians were less likely to prescribe the drug after having a patient who experienced a side effect (major bleeding) associated with warfarin. Patients treated by physicians 90 days after a negative experience were 21% less likely have a warfarin medication prescribed for blood clots as compared with patients who were treated by these same physicians before the negative experience (Choudhry et al., 2006). Singh (2021) found that obstetricians who experiences complications in one delivery mode (vaginal *vs.* cesarean) switch to the alternative one after an adverse event. Keating et al. (2017) have assessed the impact of colonoscopy complications on orders of colonoscopy among primary care physicians. Authors found that physicians who had a patient who experienced a serious adverse event from colonoscopy had a temporary decrease in numbers of colonoscopy orders for other patients (Keating et al., 2017). Ly (2019) found that after an injury report against a physician's peer, rates of advanced imaging increased in the first quarter after the report but did not persist for another quarter. In a larger study, Ly (2021) investigated impact of availability bias on physicians' rates of pulmonary embolism testing. In a sample of 7,370 emergency physicians with 416,720 patient visits for shortness of breath, Ly (2021) found that physicians who had a recent patient visit with a pulmonary embolism diagnosis were more likely to order pulmonary embolism testing for subsequent patients. In cancer screening, Wang et al (2022) found that primary care physicians after diagnosing a patient with cancer increased cancer screening recommendations for other patients.

It is hard to debias the effect of availability on judgments. One possible solution to mitigate availability heuristics and improve accuracy is deliberative reflection and assessment of presence and absence of findings supporting a diagnosis (Mamede et al., 2010). Moreover, increasing awareness of cognitive biases and their influence on judgments and decision making could serve as a possible solution.

3.2. Affect heuristic

Existing research has shown that judgments and decisions are often impacted by feelings - positive and negative affect (Slovic et al., 2007). The mechanism that explains the lack of independence in evaluation of risk and benefits is called affect heuristics, which simply explains that people tend to underestimate risks and overestimate benefits of hazards (activities or technologies) that they *like* and overestimate risks and underestimate benefits of *unliked* hazards. For example, Fischhoff and collaborators (1978) found that antibiotics and vaccinations are perceived as high in benefits and low in risks. Similar results were found when judging risks and benefits of stem cells therapy in cancer or abortion (Sokolowska & Sleboda, 2015). Affect heuristic can predict how individuals process information that they are presented with. For example, Sunstein (2003) found that when presented with cancer risks information participants were willing to pay more to eliminate cancer's risks when affect-rich description was added to the scenarios, as compared to raw probabilities. Scherer et. al. (2017) found that affective processes can influence how people interpret information about medical test outcomes. Keller and collaborators (2006) found that positive affect was associated with greater intention to test for breast cancer when messages were framed in a loss frame while negative affect was associated with greater intention for screening when messages were framed in a gain frame. Isen and collaborators (1991) have investigated whether induced positive affect impacts medical diagnosis made by third-year medical students and found no differences in accuracy of judgment between control and treatment group (positive affect). Authors, however, found that subjects in the positive-affect condition were making the diagnosis significantly faster than the control group.

A review paper that looked at studies on cognitive biases and heuristics in medical decision making by Blumenthal-Barby et al, (2014), listed only five papers that have tested affect heuristics in medical decision making. There are, in fact, not many empirical studies on affect heuristics and medical decision making and diagnostic delays.

3.3. Status Quo bias

Preference for the status quo over other alternatives is a common bias in human behavior. For example, people often stick with the default option of a health insurance plan and never consider the benefits of switching to a better plan. This inertia can also explain insufficient utilization of preventive health seeking behaviors such as an annual checkup and regular cancer screening. Cancer screening often requires an active choice that deviates from the current health status quo, and therefore can be avoided due to potential costs such as time, money and discomfort (Ackerson & Preston, 2009). This bias can also exacerbate health inequity as preventive healthcare is not part of the "status quo" of many underrepresented and vulnerable populations.

Element of choice architecture can also amplify status quo bias as documented by Redelmeier and Shafir (1995) who found that increasing the number of choices can influence decision difficulty. Specifically, in a study with physician participants, Redelmeier and Shafir (1995) found that physicians were more likely to stick to the default option (referral to treatment) than prescribing one of two medications. However, in identical scenarios when default was presented with only one possible medication physicians were more likely to prescribe it. In the second study by Redelmeier and Shafir (1995) neurologists and neurosurgeons were asked to choose either one out of two or one out of three patients who should undergo surgery. In the group with choices between Patient 1 and Patient 2, most doctors chose to treat Patient 1. However, if Patient 3, who was highly similar to Patient 1, was added to the list of options, the doctors preferred to choose to treat Patient 2. This pattern can be explained by decisional conflict. Decision makers desire justifications for choices they make, and these become scarcer as the number of options increases. Decisional conflict makes justification more difficult and, as a result, leads people to seek options that reduce their responsibility for the choice, such as deferral or the status quo.

3.4. Present bias

People tend to prefer immediate gratification compared with delayed. Present bias is well studied in the area of financial decision making; however, existing research has found impact of present bias in a medical context on both physicians and patients (Chapman & Elstein, 1995). For example, physicians can prioritize addressing diseases attributed to morbidity and mortality while neglecting other diseases that might be risky (Waddell et al., 2020). Decision making by physicians can also be influenced by the present biases their patients exhibit and might lead to altered treatment recommendations and non-adherence to specific treatments (Irvine et al., 2022). Despite the significance of present bias, we could not identify empirical research on the role of such bias in physician decision making.

On the patient side studies, have suggested that present bias might explain low rates of mammography screening (Fang & Wang, 2015) and low medication adherence rates among patients with diabetes (Y. Wang & Sloan, 2018). Present bias was mostly studied in the area of smoking and other addictive behaviors (Ida, 2014; Khwaja et al., 2007). For example, Ida (2014) found that smokers are more prone to being present biased than non-smokers. Morkbak and collaborators (2017) reported that present bias was associated with being more likely to experience onset of diabetes at a younger age and having a poorer prognosis after diagnosis. In some psychiatric disorders, present bias (also called delay discounting) is used as a transdiagnostic measure and could be a target for treatment (Amlung et al., 2019).

3.5. Information avoidance

One understudied concept that could explain underutilization of preventive health behaviors is information avoidance. An active information avoidance occurs when individuals decide to avoid accessing the information even when they (1) are aware that the information is available (*e.g. not to get tested*), and (2) have free access to the information (Golman et al., 2017). The decision to avoid or ignore potentially useful information is common and often costly in health. An example is the active decision to not get tested, for example, when serious genetic condition or sexually transmitted disease test results could help an individual and others in future decisions (Oster et al., 2013; Sullivan et al., 2004; Thornton, 2008). Researchers have speculated that people tend to avoid information to postpone the accepting process in order to face a problem when resources to cope with the information are available (Golman & Loewenstein, 2018; Loewenstein, 2006).

People tend to seek out information in line with their pre-existing worldview and cognitive skill levels rather than acknowledge or seek new information that may cause an uncomfortable conflict in their minds (Jonas et al., 2001). Indeed, confirmation bias, that is selective information gathering and evidence analyses that confirm a diagnosis while ignoring other data (Nickerson, 1998), has been found among physicians (Redelmeier et al., 2001; Stiegler et al., 2012; Tschan et al., 2009). Gigerenzer and collaborators (2007) demonstrated that physicians avoid information that includes health statistics as their training and background lacks knowledge to understand statistics well. Hence, such behaviors might lead to omitting evidence-based practice and impact medical judgments and patients' choices (Gigerenzer et al., 2007).

4. Risk perception

Subjective risk perception of both patients and clinicians is directly affected by cognitive biases in judgment. Risk perception and understanding of risk information can be impacted by various factors, including individual differences in information processing (numeracy skills, literacy) but also by the form of the risk communication. Risk perception guides preventive health behaviors such as cancer screening (Hay et al., 2016; Peters, McCaul, et al., 2006) or vaccine uptake (Brewer et al., 2007; Okan et al., 2020).

For example, Slovic and Monahan (1995) found that presented format of the risks information influences judgments about treatment risks among both clinicians and non-experts. One study on perception of lifetime breast cancer risk showed that among women with elevated risk for breast cancer, the majority overestimate their lifetime breast cancer risk (Xie et al., 2019). Low perception of cardiovascular risk was found to be especially common among men and residents of urban areas (Homko et al., 2008). Interestingly, underestimation of cardiovascular risk was also found among high-risk cardiac patients who were admitted to a hospital for an interventional coronary procedure (Everett et al., 2016).

Studies show that format of presented information, that is verbal communication of risk vs. numerical, plays a role in understating presented information (Bruine de Bruin et al., 2000). Moreover, evidence suggests that patients hold preferences for a format of risk communication with their physicians (Mazur et al., 1999). In fact, prior work has documented that treatment preferences may be impacted by the type of statistics used to communicate risk (Bucher et al., 1994; Chao et al., 2003; Edwards et al., 2010; Forrow et al., 1992; Malenka et al., 1993; Naylor et al., 1992; Wegwarth et al., 2010). For example, a greater proportion of physicians recommended screening when making judgment based on a 5-year survival rate as compared to judgment based on annual disease-specific mortality (Wegwarth et al., 2010).

The format of risk communication can improve understanding of one's risk (Xie et al., 2019). Studies show that the format of risk communication impacts both patient and physician judgments and recommendations. Physicians were found to be more favorable toward treatment when presented with a relative risks reduction than when presented with absolute risks (Forrow et al., 1992). Presenting benefits of cancer screening as a relative risk reduction was associated with greater willingness to test as compared to when the same numbers were presented as an absolute risk reduction or numbers needed to screen (Sarfati et al., 1998). Natural frequencies were found to be easier to understand in elderly and younger patients, including low numerate individuals (Galesic et al., 2009). Analyses of the form of cervical cancer screening communication in UK websites revealed information about benefits and risks were presented in different formats making it difficult to compare, such as communication often included relative risk reductions to express screening benefits, and verbal quantifiers without numbers to express risk (Okan et al., 2019). As suggested in the literature review, interventions that aim on shifting risk perception and increase understanding of risk can lead to subsequently improved health behavior (Ferrer & Klein, 2015). Creating risk communication personalized to the targeted audience has more potential for greater success (Ferrer & Klein, 2015).

5. Choice Architecture Framework

5.1. Framing and Reminders

Framing, that is how information (e.g., risk, benefits, probabilities) is presented, can dramatically influence decision making about health. In a classical example of the effect of framing, people facing decisions over medical treatments respond differently to a description of 90% survival rate – a gain frame than they do to a description of 10% mortality rate – loss frame (Daniel Kahneman & Tversky, 1972). In the health decision context, differences in the description of the same information can determine the recommendation of treatment by doctors and selection of treatment by patients (Block & Keller, 1995; Garcia-Retamero & Galesic, 2010; Marteau, 1989). Physicians were found to make a different decision about the same health issue depending on whether they are making a recommendation for one patient vs. a group of patients (Redelmeier & Tversky, 1990), or when choosing a therapy for a flare of systemic lupus erythematosus that is predicted to last a longer vs. shorter period of time (Redelmeier & Tversky, 1992).

Framing of potential risk and benefits of vaccination can affect risk perception and intention to vaccinate. One study investigated whether framing of education leaflets (sepsis vs. traditional vaccination leaflets) resulted in differences in knowledge and risk perceptions about influenza, pneumococci, and sepsis and whether it is associated with immediate and long-term vaccination intention and behavior for pneumococcal and influenza vaccinations (Eitze et al., 2021).

Framing effects are commonly investigated in field studies that randomize content in flyers, text messages, and other forms of communication (S Huf et al., 2016, 2017). Huf and collaborators (2020) in study 1 found that receiving a text message reminder from a primary clinical physician increased screening rates from 26.4% in a control group without reminder to 31.4%. In study 2 Huf and collaborators (2020) tested the effect of reminders that are framed differently, including 1) simple reminder with no manipulation, 2) reminder - text from primary care physician, 3) reminder - text message with social norms frame presented as proportion, 4) reminder - text message with social norms frame as a total number, 5) reminder - gain frame or 6) reminder - loss frame. Authors found that all reminders, including simple without framing, increased cervical cancer screening rates (Sarah Huf et al., 2020). Fukuyoshi et al., (2021) found that easy and attractive reminders encouraging hepatitis screening among a Japanese population were associated with increased screening rates from 21.2% in the control group to 37.1% and 86.3% in treatment groups.

As seen from the examples above (Fukuyoshi et al., 2021; Sarah Huf et al., 2020) and other behavioral research, reminders can be highly effective interventions (Allgood et al., 2016; Duarte, 2021; Mayer et al., 2000; Muller et al., 2017).

5.2. Defaults and Active Choice

Defaults are one of the most powerful tools of choice architecture due to the reliance on status quo bias (Li & Chapman, 2020). For example, people who have prescheduled their flu vaccination appointments are more likely to get vaccinated than those who have not prescheduled (Chapman et al., 2010). A recent study by Milkman et al. (2021) found that priming the concepts of default by framing the reminder as “appointment was reserved for you” was the most effective to encourage flu vaccination. Moreover, defaults can help increase the reach of evidence-based programs, such as diabetes prevention programs (Aysola et al., 2018). Defaults are of particular interest in medical decision making due to the increasing reliance on EHR systems in the everyday work of clinicians. These systems are full of pre-specified defaults, recommendations, and information (i.e. choice architecture) that can be modified to improve decision making (Meeker et al., 2016)

Defaults can also be set for patients. Montoya et al. (Montoya, 2018) have investigated effectiveness of defaults and financial incentives on HIV test take-up among emergency department patients (N=8,715). Specifically, patients were cross-randomized to $0, $1, $5, and $10 incentives and to opt-in, active-choice, and opt-out test defaults. Among all the treatments, opt-out had the largest effect, followed by the $10 financial incentive. However, the effects of financial incentives ($5 and $10 treatments) were weakened in the opt-out group. Reminders can also help to set defaults. Huf and collaborators (2021) in a randomized clinical trial among underserved populations found that serial text messaging that include a pre-alert text message offering the options to opt-out of receiving a mailed fecal immunochemical test (FIT) kit, followed by up to three behaviorally informed text message reminders improved colorectal cancer screening rates by 17.3 percentage points (from 2.3% in control group that received a usual care text message reminder to 19.6% in the intervention group). The use of defaults to influence behavior is, however, subject to active ethical debate (Lorenz-Spreen et al., 2020; Schubert, 2017; Smith et al., 2013).

An alternative to setting a default is encouraging active choice among alternatives. Active choice is also a method that mitigates the potential ethical challenges of setting a default for all patients. Another study by Mehta et all, (2019) investigated effect of choice architecture on colorectal cancer (CRC) screening behaviors. Specifically, authors conducted a randomized clinical trial where participants were assigned to either of three groups: (1) direct phone number to call for scheduling colonoscopy (colonoscopy only), (2) direct phone number to call for colonoscopy and a mailed FIT kit if no response within 4 weeks (sequential choice), or (3) direct phone number to call for colonoscopy and a mailed FIT kit offered at the same time (active choice). Authors found no significant increase in CRC screening when offering sequential or active choice, but there was a lower rate of colonoscopy in the choice arms than in the colonoscopy-only arm.

5.3. Social norms

Decision makers often evaluate their own behavior by comparing it to norms and peer behavior (Meeker et al., 2016; Schultz et al., 2007). For example, vaccine uptake was influenced by vaccination behaviors of peers (Bruine de Bruin et al., 2019). The use of social norms for behavior change is related to framing, because one can frame the information about peer behavior to obtain the desired effect. In a famous study, emailing comparative information about antibiotic prescriptions to physicians was an effective tool in lowering inappropriate antibiotics prescribing for acute respiratory tract infections (Meeker et al., 2016).

Social norms – one's perception of what most people do (Cialdini et al., 1990) – have been found to be impactful in prompting desired behaviors, including vaccine uptake. Interventions that build on social norms and comparison (often called social proof) have been found to be effective in many health behaviors, such as risky sexual behavior (Sunstein, 1996), smoking, and obesity (Christakis & Fowler, 2007). Usually, interventions that build on social norms include a message indicating that a specific proportion of the population engage in a specific behavior, which therefore sends a message of what is an effective behavior (Cialdini et al., 1990).

Social norms communication was widely used in the context of vaccine uptake, and a majority of studies suggest a positive effect of social norms intervention on vaccination rates (Quinn et al., 2017). In a recent study Galizzi et al (2022) randomly assigned participants to one of seven treatment groups with different messages about the proportion of social circle that had been vaccinated, ranging from 10% to 95%, and a control group with no message. Authors found that the treatment groups, that is with social norms framing messages, have significantly greater vaccination intention than the control. Interestingly, intention to get vaccinated increased with the coverage rate up to a 75% level. When messages showed that in their social circle more than 75% of people were vaccinated, the effect of social norms remains flat or even declines. Information about peer behavior might not work as intended. For example, if a low proportion of the population engages in the targeted behavior, providing this information might further discourage behavior. Another example is potential freeriding behavior, which can be triggered when a large of enough share of the population already engage in the desired behavior (e.g., I do not need to vaccinate because 95% of the population is already vaccinated). Social norms interventions are not always effective as shown in a study of seasonal influenza vaccination by front-line hospital staff (Schmidtke et al., 2020).

Table 2. Choice architecture: definition and examples from physician and patient perspectives

Concept	**Definition**	**Example (physician)**	**Example (patient)**
Framing	Framing, how information (e.g., risk, benefits, probabilities) is presented	Presenting treatment information as mortality rate (i.e., loss-frame) versus survival rate (i.e., gain-frame)	Receiving reminder for screening framed as "message from your PCP" as opposed to neutral frame

Defaults	The default option is the course of action that the individual will obtain if they do not actively specify a particular course of action	Changing the recommended EHR system action after symptom information is provided by patient (e.g., order additional lab test)	Default to (opt-out) rapid HIV screening test unless they opt out (e.g., "you will be tested unless you decline.")
Social norms	Providing information on behavior of other (or similar) people	Emailing information about the behavior of "top physicians" on antibiotic prescription rates	Provide information on high uptake of screening test in your group or location (e.g., "last year 12,000 women in your city took part in cervical screening. Your cervical smear test is due."
Incentives	Monetary incentive can make a specific behavior more attractive and more salient	Incentivizing physicians for meeting hypertension treatment guidelines	Providing a direct payment for scheduling screening appointment
Commitments	Commitment devices set in advance can prevent self-control problem at moment of action	Triggering a decision-support tool in EHR system and forcing completion of a checklist	Automatically scheduling vaccination appointment with penalty for cancellation

5.4. Incentives

Optimal design of incentives for behavior change is an important topic in behavioral economics research (Gneezy et al., 2011). The effectiveness of financial incentives for boosting preventive health behaviors varies across incentive designs (e.g. lottery vs. fixed or condition vs. unconditional) as well across various medical contexts and environments (Dougherty et al., 2018; Kevin G. Volpp et al., 2017). Clinical trials of incentives often combined the use of incentives with other elements of choice architecture such as reminders and active choice. In the most comprehensive study to date, Volpp and collaborators (2017) investigated whether medication reminders together with financial incentives and social support delays subsequent vascular events in patients who have suffered acute myocardial infarction. In a compound intervention integrating wireless pill bottles that measured medication adherence, lottery-based incentives, and social support, authors found no significant improvement in medication adherence or vascular readmission outcomes as compared to a control group. These results are particularly discouraging for addressing the crucial behavioral challenge of medication adherence.

There is a large body of literature investigating incentives as a method to increase cancer screening rates but often with inconclusive results. For example, Gupta and collaborators (2016) have found that financial incentives, in the amount of $5 or $10, offered in exchange for responding to mailed invitation to complete FIT for colorectal cancer do not impact CRC screening completion. Mehta et al (Mehta et al., 2017) found a modest but significant increase in colonoscopy rates among subjects in the intervention group that was composed of a combination of active choice and financial incentives, while active choice alone was insufficient to encourage completion of a screening colonoscopy.

There are multiple ways to design incentives with some trials comparing different incentive mechanisms against each other. For example, a clinical trial of CRC screening adherence using FIT investigated three types of incentive mechanisms: (1) $10 unconditional incentive, (2) $10 conditional on completion incentive, and (3) 1 in 10 chance of winning $100 incentive. None of these incentive designs resulted in higher FIT completion rates (Mehta, Pepe, et al., 2019). Similarly, another large-scale clinical trial found no effect of lottery based incentives on completion of screening colonoscopy (Mehta et al., 2020). For some behaviors, incentives might not be effective at all and/or must be high enough to change behavior, often making the use of incentives not cost-effective compared to other alternatives.

Recent reviews support a skeptical view of the use of incentives to encourage cancer screening behaviors. A systematic review of the literature investigating effects of financial incentives on screening behaviors for breast, cervical and colorectal cancer (Mauro et al., 2019) found that among the included 18 studies, the majority showed partial or no effects of financial incentives on breast and cervical cancer screening rates. Only a few studies showed positive effects in CRC screening behaviors (Mauro et al., 2019). Furthermore, Facciorusso and collaborators (2021) conducted a systematic review with meta-analysis of randomized clinical trials to evaluate the relative and absolute benefit associated with adding financial incentives to CRC screening behaviors. In this review, financial incentives were associated with small increases of CRC screening behaviors with only marginal increase in underserved populations with adverse social determinants of health (Facciorusso et al., 2021).

The effect of financial incentives has also been tested in screening for infectious diseases, including HIV and chlamydia. However, also in this context, the effect of incentives is inconclusive. A large incentivized trial with non-cash financial incentives found no impact of incentives on chlamydia testing among young UK adults (Paul Dolan & Rudisill, 2014), while other studies found positive effects (Currie et al., 2013; Niza et al., 2014). Some studies obtain particularly strong effects of specific incentive designs. Niza et all (2014) tested the impact of financial incentives (£5 voucher vs. £200 lottery) framed as a gain or a loss and found that compared to the control group (1.5%), the lottery increased screening to 2.8% and the voucher increased screening to 22.8%. Framing incentives as gains were marginally more effective (10.5%) than framing incentives as losses (7.1%). To summarize such effects, a recent systematic review on incentives of screening uptake in sexually transmitted and blood-borne infections in high-income countries revealed that in high-income countries both monetary and nonmonetary incentives increase screening behaviors (Lambert et al., 2022).

Physicians are already incentivized as part of their job. Nevertheless, it is possible to use additional incentives to increase the salience of specific actions. Several studies have investigated the effectiveness of pay-for-performance incentives. Kristensen and collaborators (2014) analyzed the effect of a pay-for-performance program that was introduced for all hospitals in northwest England in 2008. Authors analyzed the effect of financial incentives paid to hospitals (not the medical team) and found that short-term financial incentives directed to hospitals were associated with mortality reduction, however, in the long run the differences were not significant. Pay for performance has been studied on an individual level. Petersen et al. (2013), investigated the effect of financial incentives directed to either physicians only, practice level (where payments were equally distributed to physicians and nurses), or a combination of physician and practice-level payments on guideline-recommended hypertension care. Authors found that incentives directed to physicians led to greater blood pressure control or appropriate responses to uncontrolled blood pressure.

One particularly interesting direction of research is using shared incentives between patients and physicians to improve important health outcomes. In this case, it is possible to incentivize outcomes as opposed to specific behavior because health outcomes are often a result of both physician and patient behaviors and actions. Asch et al., (2015) investigated whether physician financial incentives, vs. patient incentives or shared incentives were more effective than a control group (standard treatment no incentives) in reducing low-density lipoprotein cholesterol (LDL-C) among patients with high cardiovascular risk. In this study, physicians were eligible for a $1024 incentive per enrolled patient who met LDL-C goals. Patients in the patient incentive group could enter a daily lottery only on the days when they adhered to the medication, with an overall total expected incentive amount of $1024. In the shared incentives group, each were eligible for half of the incentive, $512 – physicians when the patient met the LDL-C goal and patients in daily lotteries. No incentives were introduced in the control group for physicians, while patients received up to $355 each for trial participation (lottery based). Results showed that only shared physician-patient incentives had a significant effect on patients' reductions in LDL-C levels (Asch et al., 2015). This paper was recognized as paper of the year in 2016 by AcademyHealth for a significant contribution to health services research and health policy.

5.5. Commitments

As health behaviors are affected by self-control, commitment devices are a tool to mitigate suboptimal decision making around health and to help overcome present bias. One way to leverage commitment and avoid present bias is offering patients choices about future behavior, before the time that they have to take an action (Rogers et al., 2014). For example, patients can be contacted to schedule regular exams or labs well ahead of time and accept a financial penalty for canceling within a certain time

(Loewenstein et al., 2007, 2012). Financial commitment devices have been studied in promoting healthy behaviors, including smoking cessations (Gine et al., 2010), alcohol consumption (Schilbach, 2019), and physical activities and gym attendance (Royer et al., 2015). Unfortunately, research has shown that often financial penalties for not following through with a behavior that one committed to are too low and therefore the commitment is too week to overcome one's self-control problems (John, 2020).

One effective commitment device is just setting an appointment for patients. One study found that appointments were much more effective than financial commitment devices in HIV testing behaviors of high-risk men in Malawi (Derksen et al., 2021). Another study found self-commitment had no effect on HIV testing rates (Macis et al., 2021). In some settings, it is possible to encourage patients to specify when, where, and how they would make the appointment (Milkman et al., 2013). In the context of cervical smear testing, this planning prompt intervention was associated with greater screening uptake (92%) as compared to the control group (69%) (Sheeran & Orbell, 2000). In general, the underlying choice architecture of appointment scheduling in the US healthcare systems is full of unnecessary friction, making it very difficult for patients to act in their best interest under time constraints. There is a need for structural changes to make appointment scheduling easier for all patients, by making low-tech solutions accessible to all, and introducing web-based medical appointment systems whenever possible (Zhao et al., 2017).

6. Social Determinants of Health

The role of social determinants of health and challenges of health equity in the US are well documented (P. Braveman et al., 2011; P. A. Braveman et al., 2011). Disparities in healthcare have been attributed partly to clinician-level factors, including implicit bias (Maina et al., 2018). For example, implicit bias has been shown to impact women receiving fewer treatments for cardiovascular disease compared to men, while individuals of racial and ethnic minorities have been perceived as having less pain (Maina et al., 2018). Research suggests that implicit bias can be changed with incentives, pressure, transparency, and awareness (Garicano et al., 2005; Gneezy et al., 2012; Pope et al., 2018; Zitzewitz, 2012).

Social determinants of health are also associated with patients' preventive health behaviors. Indeed, inequalities among racial and ethnic minorities exist and have been well-documented, especially in screening behaviors. For example, racial and ethnic minority groups are more likely to have never been screened for cervical cancer compared to non-minority groups (Datta et al., 2022; McDaniel et al., 2021). Research has also reported health disparities among sexual and gender minority groups, reporting lower adherence to screening recommendations (Charkhchi et al., 2019; Peitzmeier et al., 2014; Valanis et al., 2000). It is crucial to target and adapt behavioral interventions in the populations who exhibit the largest disparities. This endeavor, however, comes with a significant challenge, as these types of interventions are often less effective among minority, low-resource, and vulnerable populations (e.g. (Schneider et al., 2001)). Below we review two streams of behavioral research that can provide further insight to social determinants of health and health equity.

6.1. Individual Differences

Research in cognitive psychology has documented various individual differences that account for both cognitive biases and health behaviors. For example, individual differences in numeracy - the ability to use and understand numbers, such as risks and probabilities, which is highly correlated with education. Low numeracy was linked to poorer decision outcomes (Peters, McCaul, et al., 2006) and more bias-based judgments (Peters, McCaul, et al., 2006) even when controlling for level of education (Reyna et all, 2007), verbal intelligence (Peters, Västfjäll, et al., 2006), and health literacy (Hibbard et al., 2007). For patients, numeracy is also associated with understanding of treatment risks in both US and Europe (Garcia-Retamero & Galesic, 2009). Poor understanding of numeric risk also has been found among physicians (Forrow et al., 1992) and medical students (Sheridan & Pignone, 2002).

6.2. Psychology of Scarcity

Research on poverty has found seemingly irrational behavior in several areas of life (Banerjee & Duflo, 2007; Blalock et al., 2007), including health-related behaviors. For example, take-up rates of welfare programs are low among low-income eligible individuals (Bertrand et al., 2018). Individuals with low incomes were found to be more likely to cut back their non-emergency healthcare services (Lusardi et al., 2010). There are several potential explanations of such patterns of behavior among poor people. One explanation is the lack of human capital such as education, work experience, and financial literacy (Lusardi & Mitchell, 2014). Another explanation is the culture-of-poverty view that argues that norms, values, and attitudes of poor people diverge from others (Lewis, 1998).

Behavioral economics research suggests another alternative explanation. Mullainathan and Shafir (2013) proposed scarcity theory that explains suboptimal behaviors among poor people building on insights from psychology and economics. This theory states that the state of poverty induces scarcity of mind and in turn affects decision making and behavior. Specifically, poverty shifts focus of attention toward a scarcity-related avenue that leads to dismissal of other long-term crucial issues such as preventive healthcare. Poverty can also impede cognitive functions, specifically cognitive control and cognitive capacities, which undermine rational decision making and amplify existing biases. Studies have examined the elements of scarcity theory in both a lab environment and real-world setting (Carvalho et al., 2016; Fehr et al., 2019; Huijsmans et al., 2019; Ong et al., 2019), as well as integrating scarcity theory into broader frameworks that help to understand behaviors in a poverty setting (Cannon et al., 2019; Hamilton, Mittal, et al., 2019; Hamilton, Thompson, et al., 2019).

7. Discussion

Behavioral economics can provide insights for understanding and addressing diagnostic error and delays. Early research identified the role of cognitive biases in judgments (e.g., availability, affect) in risk perception and decision making among both patients and physicians when faced with health decisions. Across domains, subjective risk perception is considered a major driver of health decisions and outcomes (Brewer et al., 2007). Additional biases such as present bias, status quo bias, and information avoidance are influential factors of human behavior that might prevent patients from actively choosing a preventive healthcare action such as an annual checkup and scheduling cancer screening. As proposed in the book *Nudge* (Thaler & Sunstein, 2008), these types of biases can be leveraged to help an individual improve decisions, for example, by setting a default that corresponds to the best actions. As reviewed in this paper, defaults are only one example of the choice architecture tools that can be used to nudge patients and physicians.

The effect of framing is worth paying special attention to because all information and communication is framed in some way. The presented framing, whether intentional or not, can greatly influence decisions in a health context because options can almost always be framed in either a gain-frame (e.g., survival) or loss-frame (e.g., mortality). Prospect theory and loss-aversion (Daniel Kahneman & Tversky, 1979) implies greater effectiveness for loss-framed information, but some empirical research favors more user-friendly gain-framed information (Niza et al., 2014). Framing can also be used to design information that highlights social norms around desired behavior. As framing exists in every public health communication, the current public health communication around preventive health recommendations and guidelines could be redesigned to achieve the public health goals. As pointed out in prior health communication literature, such communications have to be understandable and scientifically accurate to be effective (Bruine De Bruin & Bostrom, 2013). For example, screening recommendations should present balanced information in an easy to understand format that allows direct comparisons between risks and benefits (Okan et al., 2019).

As evident in our review, behavioral economics research in health has moved from mostly hypothetical lab experiments to large-scale randomized control trials and implementation in actual healthcare settings. This can mostly be attributed to the publishing of the book *Nudge* (Thaler & Sunstein, 2008) and the establishment of behavioral insight teams (i.e., nudge units) in governments and public municipalities around the world. In the UK, for example, this process led to various large-scale nudging experiments conducted within UK's National Health Service. In the US, many healthcare providers established their own behavioral insight units (Patel et al., 2018). As shown in this review, the use of defaults, reminders, and financial incentives received the most attention in large-scale clinical trials that leverage behavioral economics in healthcare. A general advantage of using nudges is the inherent cost-effectiveness (Benartzi et al., 2017) compared to traditional interventions that rely on incentives. There is also evidence that nudging or incentivizing both physicians and patients at the same time and for the same outcome can lead to better clinical outcomes compared to targeting just patients or just physicians (Adusumalli et al., 2022; Asch et al., 2015).

Despite huge progress in applied behavioral economics research in healthcare, major challenges remain. This is perhaps most evident by the failure to obtain any significant improvement in medication adherence even with an intervention that included reminders, financial incentives, and social support (Volpp et al., 2017). Similarly, while incentives work well in some settings, such as encouraging health behaviors, application of incentives for preventive healthcare (e.g., cancer screening) only shows modest effects on behavior (Facciorusso et al., 2021; Mauro et al., 2019). A major challenge is the existing friction in the underlying choice architecture that patients (e.g., scheduling appointment in patient portal) and physicians (e.g., EHR system) face. Excessive friction in the existing choice architecture can undermine the effectiveness of nudges and other behavioral interventions. While some general rules translate across choice environments, such as simplification and reducing friction, other modifications might not work as intended. There is an extensive behavioral economics literature that demonstrates failure of nudges (Fox et al., 2020; Sunstein, 2017). In the case of diagnostic delays and errors, it is important to note that diagnostic environments (e.g., emergency department, inpatient unit, primary care physician's office) substantially differ from each other and some elements of choice architecture might work in one environment but not in others. For example, primary care visits by diabetes patients with low socioeconomic status address a large and diverse set of problems in each short visit (Bolen et al., 2016) making the design of helpful choice architecture in these settings extremely challenging.

Behavioral economics research can potentially inform interventions for all levels in the healthcare system from individual patients to healthcare providers and government agencies (Matjasko et al., 2016). It is important to identify the bottleneck that leads to delay in diagnosis in each medical context and design solutions accordingly. This bottleneck can be patient-driven or provider-driven or some combination of both. In many cases, there are systemwide solutions that need to be addressed before turning to nudging individuals (Chater & Loewenstein, 2022). In medicine, time pressures during medical encounters and decision fatigue are areas of concern due to the tendency of such settings to amplify biases and reduce the quality of medical decisions (Meeker & Doctor, 2017; Silber et al., 2019). For example, a recent paper demonstrated a significant deviation from medical guidelines in pain management that appear only during night shifts (Choshen-Hillel et al., 2022). Addressing system-level changes seems a necessary step to improve healthcare quality. There are significant bottlenecks on the patient side as well. For example, scheduling an appointment for colonoscopy might be extremely difficult even when patients are motivated to get the procedure. These patients' barriers are usually amplified in rural settings and among low socioeconomic status population ns without health insurance. For example, in some areas of the US, it is extremely difficult to get an appointment with a psychiatrist or therapist to diagnose and treat mental illness (Cook et al., 2017). Behavioral economics can also be used to evaluate current public health policy, as these already often include some form of communication, nudges, and incentives (Loewenstein et al., 2012).

One promising direction for behavioral research is integration with EHR and patient portals. For example, adjusting the default setting and providing reminders for physicians in the EHR system at the point of care can be highly effective and easily implemented and scaled. A recent randomized trial showed that reminders on patient portals is an effective strategy to augment traditional mailed outreach for cancer screening (Goshgarian et al., 2022). On a broader level, a recent perspective of state-of-art healthcare (Waddell et al., 2020) argued that insights from behavioral science, choice architecture in particular, paired with scalable technology can improve health outcomes and decision making by physicians and patients. The authors further argued that in cardio-oncology, technology can be effective only if implemented with the use of behavioral science principles (Waddell et al., 2020). For example, EHR systems allow review of records of high-risk patients for potential referrals, but this cannot be effective without a planning prompt or commitment that will encourage this practice. Lau-Min and colleagues (2021) have proposed that EHRs together with principles from behavioral economics can be used to advance health equity in precision oncology.

In leveraging EHR technology, another future direction is developing algorithms and decision support systems to augment decision making at the point of care and therefore prevent errors. Diagnostic judgments are prone to human error and often result in large variability (i.e. noise) (D Kahneman et al., 2021). That is, faced with the same patient and information, different doctors make different judgments about whether patients have cancer, heart disease, or a mental health condition. In fact, the substantial variability and error in clinical judgment of mental health motivated much of the earlier work in the field of judgment and decision making. As reviewed in the heuristics and biases section, judgments are subject to a variety of heuristics that could undermine subjective diagnostic judgment. One of the most important conclusions of this research is the recommendation to rely on objective decision tools and algorithms to improve subjective judgment and clinical decisions in practice (Meehl, 1954). Since this early work in the 1950s, there have been considerable advances in the use of predictive models in medicine as a method to overcome biases in judgment and contextual effects that can lead to human error. This is mostly due to the big data revolution that transformed medicine (Obermeyer & Emanuel, 2016). One of the most recent and novel applications of machine learning models is successful early detection and alert systems for sepsis based on EHR data (Adams et al., 2022; Calvert et al., 2016). This is just one example of a larger body of work that develops algorithms to improve medical decisions making. It is important to note that algorithms in healthcare might also be biased due to a variety of challenges in the training data and the design choices (Chen et al., 2021).

The current paper has several limitations. Our review is not exhaustive and might have omitted behavioral factors that can explain or influence diagnostic delays. In terms of biases selection, as mentioned earlier, we selected the five most relevant to cognitive science biases from the field of judgments and decision making that falls under the umbrella of behavioral economics. Other biases were not discussed, except for the implicit bias discussed in the section focusing on social determinants of health. The field of behavioral science is vast and multidisciplinary, and there is an increase in behavioral science in public health research. For example, a review of cancer screening interventions identified 32 different behavioral theories that were applied to design interventions for a cancer screening (Acharya et al., 2021). Other frameworks were also proposed to synthesize behavioral effects and inform design of behavioral interventions (P. Dolan et al., 2012; Michie et al., 2011). Finally, the evidence for the role of behavioral economics in diagnostics delay is stronger in some clinical contexts, such as cancer screening, and substantially weaker in others, such as infections. Behavioral economics principles of human behavior are often universal and translate across context, but additional empirical research is needed to expand application of the field to diagnostics delays and errors.

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